

Statistical Common Author Networks (SCAN)

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A new method for visualizing the relatedness of scientific fields is developed that is based on measuring the overlap of researchers between fields. It is found that closely related fields have a high propensity to share a larger number of common authors. A methodology for comparing fields of vastly different sizes and to handle name homonymy is constructed, allowing for the robust deployment of this method on real data sets. A statistical analysis of the probability distributions of the common author overlap that accounts for noise is carried out along with the production of network maps with weighted links proportional to the overlap strength. This is demonstrated on two case studies, *complexity science* and *neutrino physics*, where the level of relatedness of fields within each area is expected to vary greatly. It is found that the results returned by this method closely match the intuitive expectation that the broad, multidisciplinary area of *complexity science* possesses fields that are weakly related to each other while the much narrower area of *neutrino physics* shows very strongly related fields.

I. INTRODUCTION

Understanding the growth and evolution of academic research fields[1, 2] is important to assessing the health and influence of scientific areas and can provide potentially important predictive capability in assessing technologies that may emerge from fundamental and applied research. A consequence of the large and growing number of highly specialized research areas is that identifying the productive intersection of these[3] can no longer be done manually. However, the ready availability of computing power, the large frequency of published work and the relatively high data integrity of bibliographic databases provides the elements necessary for automated screening and visualization of these areas.

The visualization of research areas is an active area in bibliometric studies[2, 4], largely using clustering of individual units to describe the relatedness of research areas. The primary metric conferring this relatedness has historically been the citation frequency[5], with the individual unit of measure being an instance of one publication citing another. Using publications as nodes, a very complicated unweighted directed network could be formed relating publications together. Since this is visually confusing, the practice of re-assigning these nodes as either authors or journals[6] is preferable, resulting in a weighted network map where the clustering observed in these networks broadly reflects the topical areas of study. Intuitively, these methods work well at understanding the relatedness of topical areas because authors tend to cite research in the area of their study more frequently and journals tend to publish work that caters to a specific, topically focused scientific community. Of value in these visualizations are the areas of study that lie between topical clusters that represent interdisciplinary research, which can often give rise to emerging scientific areas.

While the methods described above use citation as the fundamental unit of measure, we offer an alternative approach by showing how counting the occurrences of the same author working in multiple fields can provide the necessary linking

to relate these multiple fields to each other. Intuitively, this approach is motivated by the observation that scientists working in one area of study will work in related areas of study more frequently than in unrelated areas, and so we expect a stronger connection between closely related areas. The approach we carried out produces an undirected, weighted network map that differs from the practice described above in the following ways: (1) the nodes themselves are the topical areas of study, (2) the weight of the link connecting one node to the next is proportional to the number of authors shared between those topical areas, and (3) the clustering observed will define a major topical area composed of closely related topics. One of the values of using common authors over citations is that the links observed are much stronger since they require authors to develop deep expertise in these areas in order to publish successfully in them, as opposed to a simple understanding of the work executed, which is the minimum requirement to cite another's work in the case of citation patterns. In this paper, we develop the procedures for establishing this link, in particular correcting for name homonymy in a statistical way.

For our case studies to demonstrate this methodology we selected two extremely different areas: the *complexity sciences* and *neutrino physics*. While the latter is a traditional, narrow field of study that is deeply rooted in physics, the former is a multidisciplinary field that intersects with many other scientific areas, drawing upon the talents of many different types of scientists. For this reason we intuitively anticipate a stronger degree of relatedness in *neutrino physics* than *complexity science*, and show that the method we developed confirms that intuition. Last, we point out that while a significant number of methods in bibliometrics focus on relationships between authors and papers (i.e. co-authorship[7] or citation patterns) that elucidate the structure and pattern *within* these fields, this approach focuses on the relationships *between* these fields.

II. METHODOLOGY

The publications used to generate the common author graphs were drawn from the Institute for Engineering and Technology's Inspec publication database as accessed through

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the Thompson Reuter's ISI Web of Knowledge v5.5 index. Inspec possesses broad coverage over the fields of physics, mathematics and computer science. Once the Inspec database was selected through the Web of Knowledge search interface the Boolean keyword or series of keywords best representing the sub-field under investigation were entered into the Inspec search field. The search was performed over the years 1969-2012, the longest time span available in the database, however the vast majority of searches returned results with shorter durations. Each keyword search typically returned 10^1 to 10^5 publications. A custom Python script was written and used to pre-process the database by sub-fields to extract a list of authors, where the last name and initials were stored, and repetitions were removed. This produced a list of unique authors for every keyword search. These lists were then compared with each other to determine the number of authors the lists had in common. A symmetric matrix of pairwise comparisons was generated in this way using fast search algorithms in Python. Typical computing times were on the order of a few minutes for the generation of individual topics lists, while the overlap between topics required on the order of several hundred searches over the sub fields and took approximately half an hour, using server-class hardware.

III. DISCUSSION

As a first approximation to quantifying the link between any two fields of study one can postulate the number of authors common to both fields. Unfortunately this naive approach suffers from two deficiencies that precludes its use as a measure of overlap: field size dependence and noise. Intuitively, it can be reasoned that the number of common authors depends on first order in some way on (1) the number of authors in each topic which varies by several orders of magnitude based on field size, and (2) the probability of false positives that arise from matching two authors that are different people with the same last name and initials. These occurrences, though rare, cannot be eliminated easily and are globally present and mostly uniform. For these reasons they will be referred to as noise arising from name homonymy, which is a persistent problem in bibliometrics[8, 9]. Below, we develop a treatment for both of these effects.

First, we develop a treatment to deal with the large variation of field sizes that will affect the number of common authors in the pairwise matching. Let us consider a pool of names and from it extract two lists of names, N and M , containing n and m elements respectively with the restriction that $n \leq m$ and that the names be unique within the lists, but not necessarily between each other. Let us start by comparing one element of N to one of the elements in the list of M . There are two outcomes: the element either matches an entry in the list with probability p , or it does not (with probability $1 - p$). Since there are m elements in M , the probability of finding no matches between the first element in N to the *entire* list of M will be $(1 - p)^m$. However, we are not interested in the case of no matches, but in the case of matches, that can now be approximated by: $1 - (1 - p)^m$, as the probability that a single

element in N will match an element in list M . Now we proceed to develop an expression for comparing the entirety of both lists to each other. As a first approximation we can multiply the probability of the single element matching case by the number of elements, n , to produce the expression in Equation 1, where $\langle k \rangle$ is the number of expected matches between the lists.

$$\langle k \rangle = n(1 - (1 - p)^m) \quad (1)$$

For our purposes, the unknown variable is p , which allows us to re-arrange Equation 1 to

$$p = 1 - \left(1 - \frac{\langle k \rangle}{n}\right)^{\frac{1}{m}} \quad (2)$$

The above equation is a convenient expression but is still an approximation since every time there is a match, the number of elements used in the comparison of m will be reduced and because each element in M is unique, then it follows that subsequent matches will not contain any of the prior matched elements. Therefore since the range is smaller, the probabilities must be adjusted every time there is a match. In order to validate our use of Equation 2, we carried out a Monte Carlo simulation of the exact solution over the range of n and m within the lists used in this study by generating matches between list for different values of p , computing an average number of matches $\langle k \rangle$, and trying to recover the initial value of p by using Equation 2. The result is that for sizes within the ranges used, there was less than 5% error between the Monte Carlo result and the analytical expression on Equation 2, confirming our use of the latter as a valid approximation.

Now that an expression for the matching probability has been developed, it can be used as a measure of the strength of the link between various fields of study, which describes the overall probability that authors in one field will also publish in the paired field. While that is the focus of this study, it is first important to characterize the amount of noise arising from name homonymy. The statistics arising from the matching probabilities as calculated from the number of matched authors (the pairwise comparison matrix described in the methodology) can be used to determine this noise factor. To do this, we choose pairs of fields in which we intuitively expect to find no true overlap of common authors, implying that the overlap found is due solely to name homonymy. Specifically, we apply Equation 2 to the pairwise comparison of 25 fields within *neutrino physics* to 25 fields within *complexity science*. This produces a matrix of values of matching probability that describe the occurrence of name homonymy. We plot the histogram of these values in Figure 1, Top. The histogram shows a very tight distribution of probabilities with a very Gaussian-like distribution. In order to validate this against ground truth, the list of authors identified in this way was randomly spot-checked by using the open source search engine Google along with the affiliations listed in their papers to find the specific individuals. It was verified that nearly all of the common authors found in this way corresponded to two

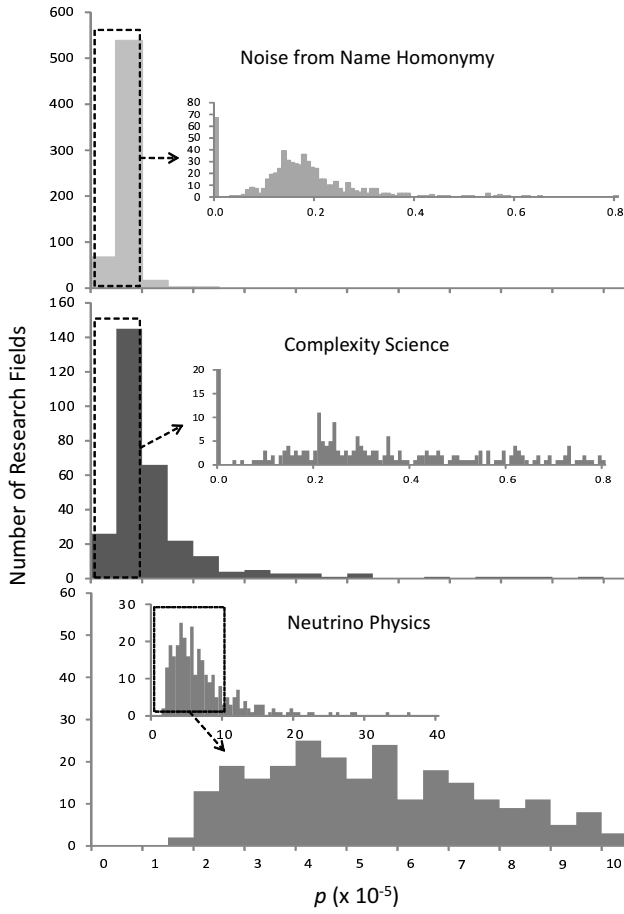


Figure 1: Histograms of scientific fields surveyed plotted as a function of the matching probability between fields of study (p) as calculated in Equation 2, using bins of the same size for comparison. Top: Probability values between areas in *neutrino physics* and *complexity science* is representative of name homonymy error. Middle: Probability values for *complexity science*. Bottom: Probability values for *neutrino physics*. Note that insets in Top and Middle show higher resolution (more bins over a smaller range) while the inset of the Bottom shows wider range (more bins but also at a much wider range).

or more distinct individuals, thus lending support to our assertion that this is a reasonable method to estimate the level of name homonymy.

Similar statistical analyses were then carried out on the areas of *neutrino physics* and *complexity science*, comparing fields within each area inclusively. In Figure 1 Middle, a histogram plotting the matching probability values of the pairwise comparison matrix of *complexity science* is shown. It can be seen that while there is a large number of matching probability values that correspond to the peak of the name homonymy noise, there are a significant number of matches that far exceed these values by as much as five times the noise value. Still, its similarity in the peak of the distribution to noise suggests that this is a very weakly related area of study where there are very few common areas between fields. This matches well with our intuition and knowledge of *complexity*

science which tends to be strongly interdisciplinary, drawing scientists working in diverse areas such as sociology, biology, computer science and economics. Complexity scientists do not share common skillsets, training, or equipment and there remains debate on the defining elements and boundaries of their field.

In Figure 1 Bottom, a similar treatment is carried out for the field of *neutrino physics*. Here we find strong overlap between authors as exemplified by a shift in the distribution toward much higher matching probability values, as high as 40 times the name homonymy noise peak. The peak itself has shifted to somewhere between 4-6 times the noise value. This indicates that the field of *neutrino physics* is very strongly related, with a large number of scientists in one field publishing in many others. This also matches our intuition since we know that this area of study is very deeply rooted in physics, requiring very expensive specialized instruments and a much smaller, less diverse physics-oriented community. Physicists studying neutrinos have a very similar skillset and training and in fact not only use similar but sometimes the same equipment.

Now we use the statistics gathered from the noise homonymy to correct the matching probabilities within areas of studies for the undesirable phenomenon of name homonymy. Simply, we define the link strength (l) to be the matching probability (p) between fields *within complexity science* and *neutrino physics* minus the average of the matching probability (p_0) of the name homonymy *between complexity science* and *neutrino physics*,

$$l = p - \langle p_0 \rangle \quad (3)$$

A plot of the fields of *complexity science* and *neutrino physics* are shown in Figure 2, where a higher link strength is represented by the thicker line weights for the lines connecting each node.

We observe additional intuitive verification when looking at the relative link weighting. For example in *complexity science*, very thick weighted lines connect the social related areas: *social network*, *social simulation*, *social systems*, *social cybernetics*. Additionally, areas where there is little connection also bears out our expectations. For example, the only field connected to *particle swarm* is *swarming behavior*, as expected. Fields which are subsets of each other also possess strongly weighted links as expected. For example in *neutrino physics*, there is a very strong link between *beta decay* and *neutrinoless double beta decay*, as papers (and therefore authors) of the former field also contain papers from the latter since the keyword of the former is included in the latter.

We have described the development and execution of a novel method in visualizing scientific fields by looking at common authors, which is valuable in the study of emerging interdisciplinary areas. The links of this network are a function of how easily the methods and training in one field can contribute to work in a related area. Compared to other knowledge mapping methods that look at patterns in citations and collaborations, this method is much more selective as common authorship can only occur an authors has a depth of expertise to allow him or her to publish original work in multiple

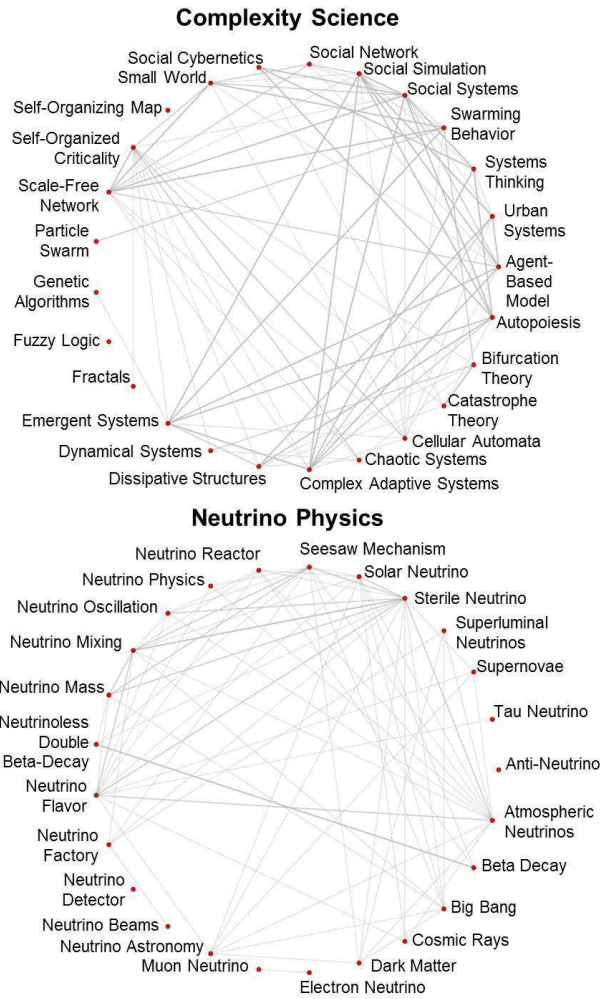


Figure 2: Network structure of *complexity science* (top) and *neutrino physics* (bottom) showing the relatedness of fields of study (nodes) as determined from the number authors that are common to each field of study. The thickness of the lines represents the link weight and is proportional to the matching probability between fields. Note that for clarity, the link weights are consistent within the top and bottom figures but not relative to each other; if done this way, then the lines in the top graph will be too faint to see.

fields. A comparison of mapping differences between these measures is planned for future work. Last, since our development of an approach to estimate the expected noise arising from name homonymy and the further statistical treatment of establishing link weightings resulted in an approximation, future work is planned to explore this more accurately.

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